AN IMPROVED JOINT STATISTICAL TEXTURE DISTINCTIVENESS METHOD FOR MELANOMA DETECTION

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***Abstract*— Melanoma is a leading cause of cancer mortality in most of the countries, resulting in one people dying every 60 mins. Earlier day's dermatology was user to detect melanoma. Due to cost expense on screening every patient, there is a need for an automated system to assess a patients risk of melanoma using images of their skin damages captured using a standard digital camera. In existing systems, Segmentation algorithm using the concept of TD is proposed. The entire framework is tested by using the illumination corrected image as an input to the texture based segmentation algorithm and compared with the state-of-art algorithm. A novel improved statistical texture based algorithm is proposed. A set of training sets are learned from illumination corrected image and calculate each distribution with the use of improved joint statistical texture algorithm. It can be tested by comparing lesion segmentation results and melanoma classification result to result using other state of art algorithm. The proposed algorithm can be used to find the dense and stage of melanoma. The proposed framework prunes to possess accuracy compared to all other existing algorithms for melanoma detection.**

***Key terms**:* texture, melanoma skin damage, segmentation, enhancement, filtering, texture distinctiveness.

I. INTRODUCTION

Melanoma is the most dangerous form of skin cancer. The cancerous growths develop when unpaired DNA damages to skin cells triggers mutation skin cells to multiply rapidly and form malignant tumor. The estimation of new cases in 2014 is 76,100. The texture distinctiveness captures the dissimilarities between learned representative texture distributions. To reduce the cost of screening melanoma in the general population, developments of automated screening algorithm been proposed.

Early the dermoscopy image captured by dermatoscope is used to separate the tumor area from the surrounding skin using highly accurate dermatologist-like tumor are extraction algorithm calculates a total of 428 features for the characterization of the tumor, classifies the tumor as melanoma and present the diagnosis[11]. Later many other algorithms used for diagnosing the melanoma using image processing. One challenge in implementing such a system is locating the skin lesion in the digital image. In before algorithm the entire framework is tested by using the illumination corrected image as an input to the texture based segmentation algorithm and compared with the state-of-art algorithm [1]. In many case, the lesion can be roughly separated from the background skin using a thresholding method applied to blue channels. This results in detecting lesion border in dermoscopy image using ensembles of thresholding methods [2]. Sometimes, the statistical texture distinctiveness approach is used for robustly detecting salient regions in natural images. Rotational- invariant neighborhood based textural representation is used in such cases [5].

Before extracting the features in melanoma, the damaged part of skin part is identified using the algorithms. It can be finding by some rules such as ABCDE rules. It includes asymmetry, border, color, diameter, evolving. Asymmetry is that one half of a mole or birthmark does not match the other. Border is the edges are irregular, rages, notched or blurred. Color is not the same all over and may include shades of brown or black or even patches of pink, red, white or blue. Diameter, the spot is larger than about ¼ inch across, but melanoma can be smaller than this. Evolving is changing in size, shape or color. Therefore, it is important that the skin lesion segmentation algorithms is accurate, as the resulting in finding the dense and stages of melanoma. Some algorithms such as MSIM show better visual, segmentation and classification results.

Many segmentation algorithm that uses statistical region merging and gradient vector flow snakes can locate skin lesion in image automatically.[6][8]. The segmentation algorithm for dermatological image use color information, either in a single channels or across three color channels, to find the lesion. The skin damage can be find by differentiating normal skin and lesion skin.

The improved joint statistical texture distinctiveness method is proposed based on texture distinctiveness to locate skin lesion in photographs. The main contributions are the introduction of joint statistical TD metric and texture based region classification algorithm. TD captures the dissimilarities between learned representative texture distributions. Next, the

process of learning the sparse texture model and calculating a metric to measure TD is described. As part of this contribution, here introduced the use of joint statistical information to characterize skin and lesion textures as representative texture distribution. Then, regions in the image are classified as being part of the lesion or normal skin. This region classification algorithm incorporates the texture information captured by the TD metric.

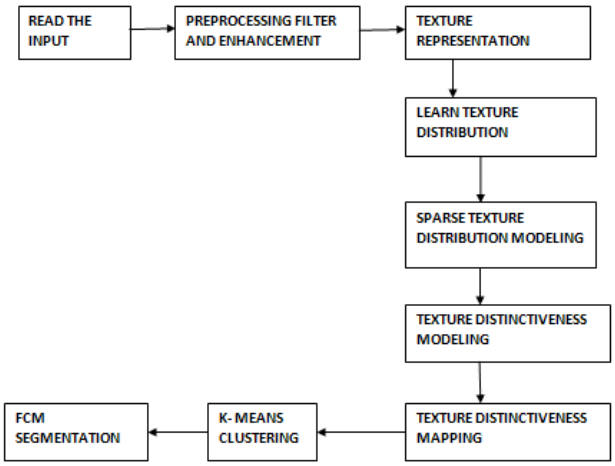
II. RELATED WORK

In [1], a set of representative texture distributions are learned from an illumination-corrected photograph and texture distinctiveness metric is calculated for each distribution. Next, regions in the image are classified as normal skin or lesion based on the occurrence of representative texture distributions. The proposed segmentation framework is tested by comparing lesion segmentation results and melanoma classification results to results using other state-of-art algorithms. The major drawback is that it just detects the melanoma but not the dense and stages. Wide range of images cannot be undertaken [1]. Multistage illumination modeling algorithm is proposed to correct the underlying illumination variation in skin lesion photographs. The first stage is to compute an initial estimate of the illumination map of the photograph using a Monte Carlo nonparametric modeling strategy. The second stage is to obtain a final estimate of the illumination map via a parametric modeling strategy, where the initial nonparametric estimate is used as a prior. Finally, the corrected photograph is obtained using the final illumination map estimate. But it Lacks in accuracy and cannot find stages of melanoma [6]. In this we describe all this steps, giving special attention to segmentation approaches for pigmented skin lesions, proposed for standard camera images (i.e. simple color photographs).Next, we compare the segmentation results to identify which techniques have more accurate results, and discuss how these results may influence in the following steps: the feature extraction and the final lesion classification. Even with the help of dermoscopy, differentiating malignant and benign lesions is a challenging task. In fact, specialists affirm that in the early evolution stages of malignant lesions, dermoscopy may not be helpful since it often does not improve the diagnosis accuracy. Still considering early stage cases, there are practical situations where a no specialist (e.g. a physician not trained on Dermatology) wishes to have a qualified opinion about a suspect skin lesion, but only standard camera imaging is available on site. In such situations, telemedicine is justifiable, and the non-specialist can capture a macroscopic pigmented skin lesion (MPSL) image of the suspect skin lesion and send it to a specialist, who can analyze it in higher detail. Since there is no standardized protocol for acquiring these images, often they contain artifacts like hair, shading and other disturbances that make the remote diagnosis by specialists more difficult. With the help of the automatic segmentation, this task may be facilitated. But the discriminating lesion and healthy skin areas may be more difficult on monochromatic images, since the chromatic aspect is lacking in them.

III. PROPOSED WORK

A segmentation algorithm is proposed based on improved texture distinctiveness to locate skin lesion in photographs. This algorithm is referred to as the improved TD lesion segmentation algorithm. The main contributions are the introduction of joint statistical TD metric and a texture based region classification algorithm. TD captures the dissimilarities between learned representative texture distributions. Next, the process of learning the sparse texture model and calculating a metric to measure TD is described. As part of this contribution the use of joint statistical information to characterize skin and lesion texture a representative texture distribution. Then, regions in the image are classified as being part of the lesion or normal skin. The region classification algorithm incorporates the texture information captured by the TD metric. Then dense and stages are find using the improved texture distinctiveness algorithm. Thus the implementation result can be obtained.

IV.FLOWCHART



IV. IMPLEMENTATION ALGORITHM

The implementation of an improved joint statistical texture distinctiveness method includes an algorithm as follows.

1. Convert the corrected image into the XYZ color space.

2. For each pixel s in iage I , extract the texture vector t_s to obtain the set of texture vectors $T = \{t_s / 1 \leq j \leq N.M\}$

3. Cluster the texture vectors in T and B to obtain the representative texture distributions.

4.Calculate probability that two texture distributions are distinct $d_{j,k}$ using

$$d_{j,k} = 1 - L_{j,k}.$$

for all possible pairs of texture distributions.

5. Calculate the textural distinctiveness metric D_j for each texture distribution.

$$D_j = \sum_{k=1}^{K} d_{jk} P(T_{kr}/I).$$

6. Apply the SRM algorithm to find the initial regions.
D
7. Calculate the region distinctiveness metric D_R for each initial region using

$$\Delta_R = \sum_{j=1}^{K} D_j P(T_R/R).$$

8. Calculate the threshold between the normal skin and lesion classes.

$$\tau = \arg\min \sigma_1^2(\tau) P(T^r/C_1(\tau)) + \sigma_2^2(\tau) P(T^r/C_2(\tau)).$$

9. Classify each region as normal skin or lesion based in the result of step 7 and 8

$$Y(R) = \begin{cases} 1, & \text{if } \Delta_R \geq \tau \text{(lesion)} \\ 0, & \text{Otherwise (normal skin).} \end{cases}$$

10. Apply a morphological dilation operator to the initial lesion classification.
11. For each contiguous region in the initial segmentation, count the number of pixels in the region.
12. As the final lesion segmentation, return the contiguous region consisting of the most pixels.

V. EXPLANATION

a. preprocessing

The image of skin lesion is taken by a digital camera. In the preprocessing phase filtering and enhancement is done. For filtering median filter is used. It is used to reduce the salt and pepper noise in the captured image using digital camera. A median filter is more effective than convolution when goal is to simultaneously reduce noise and preserve edges. Contrast enhancer is the enhancement tool used for the process of enhancing. The steps are as follows. Loading the image ,Resizing the image , Enhancing grayscale image using any of the form like imadjust, histeq and adapthisteq.

b.texture representation:

Then the input is been read and ready for further processing. At first, the texture is represented. Here the sparse texture model algorithm is used to find the global and local text characteristics. It incorporates statistical information. A local texture vector is obtained for each pixel in the image. Convert the corrected image to the XYZ color space. Extract the texture vector and the set of texture vector. With the help of texture vector the texture distribution can be calculated . The texture distinctiveness matrix can be calculated.

c. clustering:

K-means clustering is used in this proposed algorithm. It is used as an initial step in order to increase the robustness and speedup the number of iteration required for the finite mixture model to coverage. K-means clustering finds k cluster of texture data points that minimizes the sum of squared error between the cluster member and cluster mean. It does not take any probabilistic information.

d. classification:

It classifies the region of input image based on the sparse texture distribution and their associated TD metrics. Each region is identified as lesion or normal based on the texture contents of the region. The corrected image by the preprocessing are divided into large number of smaller region called oversegmentation. The proposed algorithm is efficient and used in fast classification to find which region is lesion and normal. We use the statistical region merging algorithm for oversegmentation [9]. The advantage of using SRM algorithm is that it directly takes in account pixel location and compute efficiently. There are two steps in SRM algorithm. They are region merging and sorting. Sorting is used to order the small splited regions. Merging is used to combine the sorted regions. To reduce the number of region all segments that touch the edge of the photographs are merged into a single region.

d.1. Classification based on distinctiveness:

The region distinctiveness metric for each initial region is calculated [9]. The threshold *T* between the normal skin and lesion skin are calculated.

e. segmentation:

After the classification, segmentation is performed. Here we use fuzzy c-means segmentation. To refine the lesion borders. We use methods such as morphological dilation and region selection. Morphological operation applying a structuring element to an input image, creating an output an output image of the same size. In morphological dilation the value of the output pixel is the maximum value of all the pixel in the input pixel neighborhood. in binary image, if any of the pixels is set to the value 1 , the output pixel is set to 1. Then the numbers of regions are merged to be 1. it is necessary fro feature extraction. A lesion is being analyzed in the image. to eliminate , the each number of contiguous region is counted . The contiguous region with the larger number of pixel is assumed to corresponding to the lesion class and any other region are converted to the normal skin class. Thus we can obtains the segmentation result of lesion.

VI. OVERVIEW

The propose texture distinctiveness segmentation algorithm is compared with every other previous proposed algorithm. The algorithms are TDLS algorithm, L-SRM algorithm, Otsu-R, Otsu-RGB, Otsu-PCA. All algorithms are proposed in order to clean up the contours. The comparison can be visual comparison and accuracy comparison. The

sensitivity, specificity and accuracy is been calculated during the comparison.

VII.CONCLUSION

A novel damage segmentation using the concept of improved TD is been proposed. The TD metric is calculated in order to discriminate the lesion and normal skin. The distribution of the texture in the lesion skin is represented and TD metric is calculated by differentiating them. The TD mapping is done to the segmented images using k-means clustering and FCM segmentation. The proposed framework produced the higher accuracy than the earlier proposed method . a large data collection and annotation process can be taken as the future work.

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